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Spatial Price Integration and Asymmetric Threshold Effects in Red Shallot Markets Between Urban and Rural Areas: Evidence from North Sumatra, Indonesia

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ABSTRACT

This study investigates spatial price integration and asymmetric threshold effects in red shallot markets between rural and urban areas in North Sumatra, Indonesia. Using monthly consumer price data from 2018 to 2024 across six markets, we apply Johansen cointegration, Granger causality, Vector Error Correction Models (VECM), Threshold Vector Autoregression (TVAR), Impulse Response Functions (IRF), and Forecast Error Variance Decomposition (FEVD). Results confirm long-run price equilibrium among market pairs, with VECM indicating that 38% of price deviations are corrected monthly. Granger causality reveals directional asymmetries: short-distance markets exhibit rural-to-urban predictability, while long-distance pairs show bidirectional influence. TVAR identifies a non-linear threshold near IDR 1,200/kg, above which price transmission intensifies. IRF shows rural markets adjust more slowly to shocks from urban centers, particularly beyond 180km. FEVD results indicate that rural markets account for 22-47% of urban price variance under specific spatial conditions. These findings highlight how distance, asymmetry, and threshold dynamics shape price integration in perishable crop markets. The study offers new empirical insights for spatial food market governance and supports targeted infrastructure and information interventions to promote sustainable rural-urban integration.

1. INTRODUCTION

Red shallots (Allium cepa var. aggregatum) are deeply embedded in Indonesian culinary traditions and play a critical role in the rural economy, particularly among smallholder farmers [1-3]. As both a staple food item and a key commercial crop, their price behavior has far-reaching implications—not only for household incomes but also for food affordability and broader regional food security [4, 5]. Yet, price instability across geographically dispersed markets raises pressing questions about the fairness and efficiency of price transmission from rural production zones to urban consumption hubs. These inconsistencies suggest underlying structural weaknesses in the supply chain, particularly in how price information and market signals are shared [6].

In a country as geographically fragmented as Indonesia, where topography and infrastructure vary widely, even competitive markets can exhibit persistent price gaps. Spatial market integration (SMI)—the extent to which prices in different locations move in tandem after accounting for transaction costs and time delays—is a useful lens to assess this [7-9]. Ideally, a well-integrated market allows for quick dissemination of supply and demand signals, enabling better resource allocation and promoting equity [10-12]. However, poor integration means localized shocks remain isolated, leading to unpredictable outcomes for both producers and consumers.

Empirical work across developing nations has consistently highlighted the fragile nature of SMI, pointing to weak infrastructure, limited institutional capacity, and restricted market access as persistent obstacles [13-15]. Case studies from countries like China and Morocco illustrate how rapid rural–urban transitions can destabilize traditional agricultural networks, increasing dependence on non-farm livelihoods and reinforcing structural imbalances [16, 17]. In such settings, enduring price differentials are less about geography alone and more about systemic inefficiencies that disproportionately affect small-scale farmers [18, 19]—who often contend with higher transaction costs, weaker bargaining positions, and insufficient access to timely market data [20].

In Indonesia's red shallot industry, these dynamics are particularly evident [21]. Production remains concentrated in upland rural regions like Karo and Mandailing Natal, while major demand centers such as Medan are urban and often distant [22-24]. The flow of goods between these areas encompasses more than just physical transport—it reflects an interplay of logistics, information channels, and institutional frameworks. Fragmented pricing systems, delays in market data, and weakly connected markets hinder price convergence, ultimately limiting farmers' ability to respond to demand changes or benefit from favorable price movements [25-27].

Red shallots serve as an ideal proxy for analyzing spatial market integration in Indonesia. As a highly perishable commodity with limited storage capacity, shallots exhibit immediate price adjustments in response to supply chain changes, making them a sensitive barometer for identifying spatial frictions. Their localized production in rural uplands and widespread consumption in urban centers create natural rural–urban trade corridors with observable price dispersion. Moreover, red shallots are central to both food security and farmer livelihoods, particularly for smallholders. This combination of perishability, volatility, economic significance, and spatial dispersion positions red shallots as a highly suitable crop for investigating how price signals travel through fragmented agricultural markets in developing countries. Adding another layer to this challenge is the phenomenon of asymmetric price transmission (APT), where price responses are not uniform when prices rise versus when they fall. APT is frequently linked to imbalances in market power, storage capacities, and access to information—factors well documented across global agricultural markets [28-30]. In spatial terms, these asymmetries are magnified when urban centers dominate capital and information flows, while rural producers must rely on delayed or partial signals [31]. The result is an uneven playing field, with some markets better equipped to absorb shocks than others [15].

To effectively evaluate market integration under such complex conditions, it is vital to account for both linear and nonlinear dynamics. Traditional econometric tools like VAR and cointegration models assume consistent price adjustments, potentially missing threshold behaviors. Models such as the Threshold Vector Autoregressive (TVAR) or Threshold VECM offer a more nuanced view, allowing for regime shifts when price differentials cross specific thresholds [32, 33]. These approaches are particularly valuable for understanding how transportation costs, supply disruptions, or institutional barriers shape market reactions.

Geographic proximity remains a central factor in determining the intensity and direction of market linkages. Markets closer together typically integrate more easily due to lower transaction costs and stronger information flows, while more distant markets often exhibit weaker or delayed connections. Moreover, the influence of one market on another may be asymmetric—urban markets frequently exert more sway, especially when policy, infrastructure, and demand are skewed in their favor [15, 34, 35]. Recognizing these spatial asymmetries is essential to avoid oversimplified conclusions about market behavior [36, 37].

In this light, the red shallot markets of North Sumatra provide an especially relevant case for investigation. The province presents a mosaic of agro-ecological conditions, varying levels of infrastructure, and diverse rural–urban connections. Despite the crop's economic importance and growing policy interest in food system resilience, there is still limited empirical insight into how shallot prices move across space in this region. Shedding light on these price dynamics is not just academically valuable—it's also key to crafting more equitable and effective rural development and market integration policies.

This study sets out to rigorously analyze spatial price integration and asymmetric transmission patterns between urban and rural shallot markets in North Sumatra. Drawing on monthly price data from 2018 to 2024 and using a mix of advanced time-series methods—including cointegration tests, Granger causality, VAR/VECM models, and threshold-based techniques—we aim to map out the deeper mechanics of price transmission. Special emphasis is placed on spatial distance, directionality of influence, and nonlinear responses to shocks—dimensions that are too often overlooked. Ultimately, the findings are expected to contribute to more informed policy debates around market access, rural equity, and sustainable food security.

Specifically, the study addresses the following research questions:

1) To what extent are urban and rural red shallot markets in North Sumatra spatially integrated, and what does this imply about market efficiency?
2) How do price threshold effects and spatial distance shape the nature of price transmission and shock responsiveness across markets?
3) What structural patterns of asymmetric causality exist between urban and rural markets, and how do they vary by geographic proximity?
4) How can the findings from North Sumatra inform broader strategies for building inclusive, resilient, and sustainable food systems in other developing regions with similar agro-spatial dynamics?

2. METHODOLOGY

2.1 Research design

This study adopts a quantitative explanatory approach with a descriptive econometric model, designed to examine causal linkages between red shallot price dynamics and spatial integration in rural and urban markets in North Sumatra. The methodology integrates time-series econometrics, including unit root tests, cointegration analysis, Vector Error Correction Models (VECM), Threshold VAR (TVAR), Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD). These tools allow the study to assess both short-run and long-run dynamics, while incorporating threshold and spatial asymmetries in price transmission.

2.2 Data sources and collection

Secondary data of monthly consumer prices (IDR/kg) for red shallots across six markets (urban and rural) were collected from January 2018 to June 2024. Supplementary spatial data were used to calculate road distances between markets. Data sources are detailed in Table 1.

While monthly price data were generally consistent across the study period (2018-2024), certain months—particularly during the COVID-19 pandemic (March to August 2020)—contained missing or delayed records due to market closures or reporting gaps. For gaps of one or two consecutive months, linear interpolation was applied to preserve continuity and minimize distortion in the VAR/VECM estimation. For longer disruptions, data points were excluded from estimation models but retained in exploratory analysis for contextual understanding. Additionally, diagnostic tests confirmed no structural breaks in the cointegration relationships during the pandemic period, suggesting that the underlying long-run price dynamics remained stable. This treatment balances data integrity with the need to maintain model reliability in the face of temporary exogenous shocks.

Table 1. Data sources and collection

Data Type	Source	Scope
Secondary Data	BPS, Agriculture Ministry, Local Gov	2018-2024 monthly consumer prices (6 markets)
Spatial Data	Google Maps, GIS Analysis	Road distances (km) between markets
Analytical Tools	EViews 12, Excel, QGIS	Stationarity, VAR/VECM, IRF, Mapping

2.3 Variables and operational definitions

To make the analysis more robust and easier to interpret, the prices are converted into a logarithmic form, represented as $Yt = log(Pit)$, which helps control for variance and allows changes to be understood in percentage terms. As explained on Table 2 which presents the key variables used in this study along with their operational definitions. The variable Pit refers to the red shallot price at market iii in month ttt, measured in IDR per kilogram. The first difference, ΔYt, captures monthly price changes and ensures the data are suitable for time-series modeling. Meanwhile, $dijd$ represents the spatial distance in kilometers between markets i and j, which is essential for examining how proximity influences price integration and transmission patterns across regions.

Table 2. Variables and definitions

Variable	Definition	Unit
P_{it}	Red shallot price at market i in month t	IDR/kg
$Y_t = \log(P_{it})$	Log-transformed price series for variance control	Log scale
ΔY_t	First difference to ensure stationarity	Rate of change
d_{ij}	Spatial distance between markets i and j	Kilometers (km)

2.4 Conceptual distinctions among econometric tools

To improve clarity, we briefly outline the key econometric models used in this study, emphasizing their assumptions and purposes:

- **Vector Error Correction Model (VECM):** VECM is used when price series are non-stationary but cointegrated, implying a long-run equilibrium relationship among markets. VECM separates long-run dynamics from short-run adjustments, allowing us to measure how quickly markets return to equilibrium after a shock. The Error Correction Term (ECT) quantifies the speed of adjustment.
- **Threshold Vector Autoregression (TVAR):** TVAR extends the traditional VAR framework by allowing for *non-linear* adjustments. It assumes that price responses differ depending on whether the deviation between market prices is above or below a critical threshold (e.g., IDR 1,200/kg). This is suitable for capturing *asymmetric or regime-switching behavior* in agricultural markets where small deviations may not prompt any adjustment due to frictions like transport cost.
- **Impulse Response Function (IRF):** IRF traces the time path of the effect of a one-time shock in one market on the future values of prices in another. It is particularly useful for examining *directional influence and shock persistence* between spatially connected markets, especially when combined with a stable VAR/VECM system.

Each model plays a unique role in understanding the spatial dynamics of price formation. VECM explains equilibrium and short-run corrections; TVAR detects asymmetric, threshold-bound behavior; and IRFs map inter-market responsiveness to exogenous disturbances.

2.4.1 Stationarity test: Augmented dickey-fuller (ADF)

The ADF test is used to assess the stationarity of price series:

$$\Delta Y_t = \beta_{0+}\beta_1 + \rho Y_{t-1} + \sum_{i=2}^{p} \beta_2 \Delta Y_{t-i+1} + \varepsilon_t$$

where, ρ indicates the presence of a unit root.

2.4.2 Johansen cointegration test

Cointegration among non-stationary variables is tested using the trace statistic:

$$LR_{tr}(\mathrm{r}) = -\mathrm{T} \sum_{i=r+1}^{n} ln\,(1-\lambda_i)$$

where,

LR_{tr}(r)=Trace test statistic

T=Number of observations

r=Number of cointegrating vectors under the null hypothesis

n=Number of endogenous variables

λ_i=Estimated eigenvalues from the Johansen system

2.4.3 Granger causality

To test directional influence:

$$\Delta Y_{1t} = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_1 y_{t-1} + \beta_1 x_{1,t-1} + \ldots + \beta_1 x_{-1} + \varepsilon_t$$

2.4.4 VECM model

Used for cointegrated, non-stationary data:

$$\Delta Y_t = \alpha\left(\beta' Y_{t-1}\right) + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t$$

where, $\alpha(\beta' Yt-1)$ is the error correction term (ECT).

2.4.5 Threshold var (TVAR)

Used to model non-linear, asymmetric price behavior:

$$Y_t = \begin{cases} \Phi_1 Y_{t-1} + \varepsilon_{1t}, & \text{if } s_{t-d} \le \tau \\ \Phi_2 Y_{t-1} + \varepsilon_{2t}, & \text{if } s_{t-d} > \tau \end{cases}$$

where,

Yt=Price series at time t

Φ_1,Φ_2=Regime-specific autoregressive matrices

s_{t-d}=Lagged price spread as the threshold variable

τ=Threshold value

ε=Error term (shock)

2.4.6 IRF and FEVD

IRFs trace the time-path of responses to one-unit shocks in other markets. FEVD partitions the forecast variance in one market attributable to innovations in others, allowing for inter-market dominance analysis.

2.5 Model validation

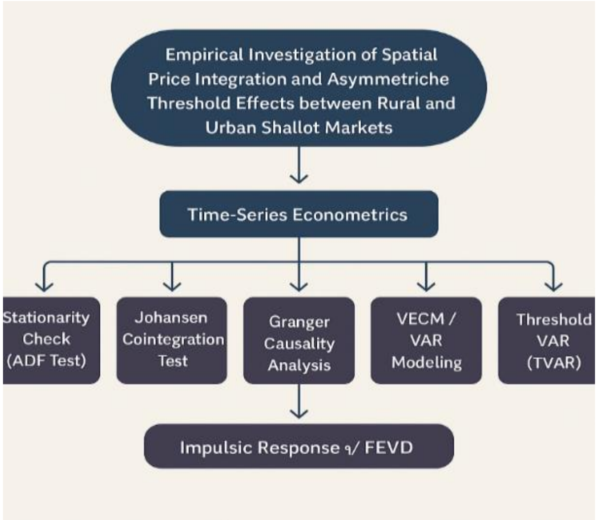

Figure 1. Methodological framework

- ADF Test for stationarity
- Johansen Test for cointegration
- VECM diagnostics (serial correlation, heteroskedasticity)
- IRF response stability
- Lag length selection via AIC, BIC
- Variance decomposition robustness checks

The complete methodology is visually summarized in Figure 1 (see conceptual framework diagram).

3. RESULTS AND DISCUSSION

3.1 Stationarity test of red shallot prices

Stationarity is a fundamental requirement in time-series modeling to avoid spurious regression. The augmented dickey-fuller (ADF) test was applied to determine whether each market's red shallot price series was stationary at level or required differencing.

The test revealed that prices in five markets—Medan Sentral (STR), Medan Petisah (PTS), Karo, Humbang, and Mandailing Natal—were stationary at level. To illustrate this, Table 3 below summarizes the ADF test results for key series in their first-differenced form, confirming their integration order I (1):

The confirmed stationarity at first difference justifies the use of VECM modeling for pairs involving Dairi, particularly in testing long-run price co-movement with Medan markets.

Table 3. Stationarity test results (First difference ADF test)

No.	Variable	ADF Test Statistic	1% Level	5% Level	10% Level	Prob	Conclusion
1	PTS	-8.720077	-3.519050	-2.900137	-2.587409	0.0000	Stationary
2	STR	-7.700473	-3.520307	-2.900670	-2.587691	0.0000	Stationary
3	DRI	-8.030232	-3.520307	-2.900670	-2.587691	0.0000	Stationary

3.2 Stability and lag structure in VAR models

To ensure the reliability of the IRF and FEVD outputs, stability testing was performed on each Vector Autoregressive (VAR) model using the roots of the characteristic polynomial. The VAR model is considered stable when all roots lie within the unit circle (i.e., absolute value < 1). This condition indicates that the system will return to equilibrium after a shock, validating subsequent simulations.

Table 4. VAR stability test results

No.	Market Pair	Root Modulus Range
1	Medan–Karo	0.74903–0.26947
2	Medan–Dairi	0.37144–0.10551
3	Medan–Humbang	0.72328–0.33331
4	Medan–Mandailing	0.70151–0.32669

The test results (Table 4) confirm that all market pairs have stable VAR structures, with maximum moduli below 1. Therefore, IRF and FEVD simulations are statistically valid and reliable for economic interpretation. Additionally, lag length selection based on the Akaike Information Criterion (AIC) shows that:

- Shorter spatial distances (e.g., Medan–Karo) required longer lag (3 months), suggesting frequent interaction and faster adjustment.
- Distant market pairs like Medan–Dairi or Medan–Mandailing showed shorter optimal lags (1-2 months), possibly due to delayed responses to shocks.
- Lag structure and system stability vary by market proximity, with closer pairs demonstrating more rapid price adjustments.

3.3 Long-run equilibrium: Johansen cointegration

According to Johansen's criteria, a market system is cointegrated when the trace statistic and/or maximum eigenvalue statistic exceed the 5% critical value. The test was performed specifically for the market pair Medan (PTS and STR)–Dairi, representing an urban–rural spatial configuration.

The results confirm that both the trace and max-eigen statistics exceed the critical values at all levels of hypothesized cointegration ranks. Therefore, it is concluded that the Medan–Dairi market pair exhibits strong cointegration, implying long-run price alignment (Table 5).

Table 5. Johansen cointegration results for Medan–Dairi markets

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	5% Critical Value	Conclusion
None	138.5610	57.97825	29.79707	Cointegrated
At most 1	80.58278	44.15829	15.49471	Cointegrated
At most 2	36.42449	36.42449	3.841465	Cointegrated

Although short-term fluctuations exist, red shallot prices in Medan and Dairi adjust toward a shared long-run equilibrium. If urban prices rise persistently, rural prices in Dairi eventually follow—highlighting a robust integration pathway between production and consumption nodes in the regional supply chain.

3.4 Spatial causality patterns

To examine the directional influence between urban and rural red shallot markets in North Sumatra, the Granger causality test was applied (Figure 2). This statistical method assesses whether past values of one time series can predict current values of another, indicating a potential causal relationship.

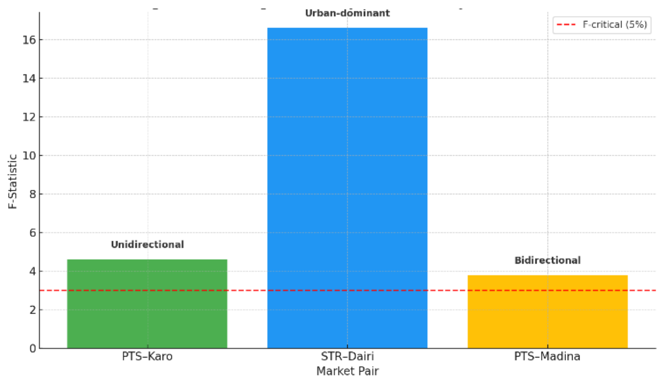

Figure 2. Granger causality f-statistics by market pair

The test results are summarized in Table 6 below:

Table 6. Granger causality test results

Market Pair	Direction	F-Statistic	P-Value	Conclusion
PTS–Karo	KRO→PTS	4.60716	0.0054	Unidirectional
STR–Dairi	STR→DRI	16.6083	0.0000	Urban-dominant
PTS–Madina	Bidirectional	3.77737	0.0276	Bidirectional

PTS–Karo: Granger causality runs from the rural Karo market to the urban Petisah market, implying that rural prices help predict short-term urban price dynamics in nearby markets.

STR–Dairi: Urban Medan Sentral statistically Granger-causes price movements in rural Dairi, suggesting a predictive influence from urban to rural markets in longer-distance settings. This reflects possible centralization in price information flows, though not necessarily pricing control.

PTS–Madina: Bidirectional Granger causality at a long distance (468km) suggests mutual short-term predictability and signals partial integration, despite geographic constraints.

These results highlight the spatial asymmetry in information transmission, where directionality and intensity of influence are shaped not only by distance but also by market role, connectivity, and infrastructural links.

The causality analysis employed reflects Granger-based temporal dependence, indicating directional relationships within the time-series framework. These should be understood as indicative of inter-market influence rather than conclusive structural causation.

3.5 VAR estimation results

This section presents the Vector Autoregressive (VAR) model estimates for market pairs with stationary price series and significant Granger causality. The analysis focuses on three key inter-market relationships: Medan–Karo, Medan–Humbang, and Medan–Mandailing Natal.

3.5.1 Medan petisah (PTS)–Karo (KRO) pair

This pair showed unidirectional causality from Karo to PTS. The VAR model indicated significant influence of Karo's lagged prices on Petisah.

Equation:

$$\begin{aligned}\mathrm{PTS}_t = 13017.01 + 0.4877\, PTS_{t-1} + 0.0663\, PTS_{t-2} \\ - 0.0953 PTS_{t-3} + 0.6219\, KRO_{t-1} \\ - 0.8095\, KRO_{t-2} + 0.3137\, KRO_{t-3} + \epsilon t\end{aligned}$$

- All significant lags have t-stat >1.6657.
- A 1% increase in Karo price→3.2% increase in PTS next month.

3.5.2 Medan sentral (STR)–Humbang (HBG) pair

This VAR result supports the presence of bidirectional price interdependence, as both markets exhibit significant lagged effects on each other.

Equation:

$$\mathrm{HBG}_t = 6850.28 + 0.5122\, STR_{t-1} + 0.3559 HBG_{t-1} + \epsilon t$$

- *STR* influences HBG significantly (t=3.09), and *HBG* has feedback effect (t=2.60).
- This supports robust spatial connectivity.

Table 7 summarizes the significant Vector Autoregressive (VAR) relationships among the studied markets, highlighting the direction and strength of price influences. The results show that the Karo market (KRO) strongly influences Medan Petisah (PTS) across three consecutive lags, indicating a strong rural push effect where local production drives nearby urban prices. In contrast, Medan Sentral (STR) exerts dominant influence on Humbang (HBG), reflecting an urban pull dynamic in this market pair. Meanwhile, Mandailing Natal (MAD) has a weaker but noticeable delayed effect on PTS, suggesting long-range rural feedback due to distance and logistical frictions. Lastly, PTS influences STR over a short lag, but the effect is relatively modest, indicating limited short-range feedback between these two urban markets.

Table 7. Summary of significant VAR relationships

Market Pair	Influencing Market	Significant Lags	Interpretation
KRO→PTS	KRO	t-1, t-2, t-3	Strong rural push effect
STR→HBG	STR	t-1	Urban pull dominates in this pair
MAD→PTS	MAD	t-2	Weak long-range rural feedback
PTS→STR	PTS	t-1	Weak short-range feedback

3.5.3 Medan – Mandailing natal (MAD) pair

A more complex structure with partial and weak links.

- PTS model: MAD prices (t-2) significantly affect PTS (t=2.45).
- STR model: Only STR's own lags are significant; MAD influence is minimal.

This reflects weak long-distance feedback from rural MAD to urban STR but shows some delayed effect on PTS.

Figure 3 compares the actual red shallot prices with those predicted by the VAR model. The strong model fit confirms predictive robustness for this market pair.

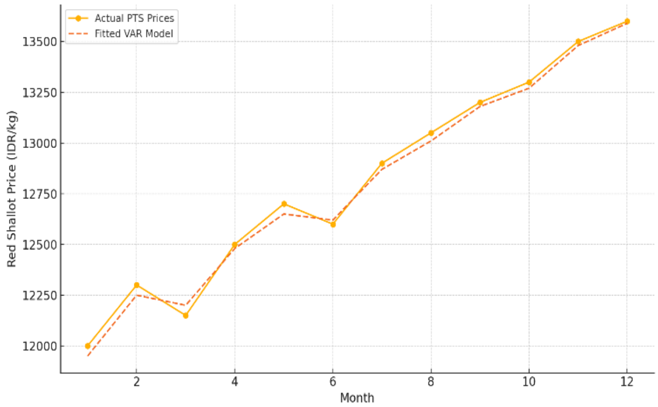

Figure 3. Actual vs fitted prices (Medan Petisah–Karo)

3.6 VECM estimation for Medan–Dairi

The VECM model is applied to the Medan–Dairi market pair due to non-stationary price series at level but cointegration confirmed via Johansen test. This model captures both the long-run equilibrium correction and short-run price adjustments.

Long-Run Dynamics

Equation:

$$\mathrm{D(PTS)}_t = 7.36 + 1.00.D(PTS_{t-1}) + 3.66.D(STR_{t-1}) - 2.94.D(DTR_{t-1}) + \epsilon t$$

- Medan Petisah prices are positively influenced by Medan Sentral and negatively by Dairi in the long run.
- Strong urban center pull (Medan STR) and rural compensation effects.

Table 8 presents the short-run dynamics from the VECM regression summarizing the estimated coefficients and t-statistics for short-run variables in the VECM model.

These values indicate that all short-run terms are statistically significant, with the strongest influence from STR (urban Medan). The negative ECT confirms a rapid adjustment toward long-run price equilibrium when short-run imbalances arise.

Table 8. VECM short-run dynamics–Medan-Dairi

Variable	Coefficient	t-Statistic	Significance
ECTt-1	-0.3162	-4.32	Yes
D(PTS)t-1	-0.4071	-3.26	Yes
D(STR)t-1	0.8314	3.76	Yes
D(DRI)t-1	-0.2968	-2.23	Yes

3.7 Threshold effects: Non linear price transmission

By separating the data into two regimes—below and above a specific threshold in the price gap—this model captures how markets respond differently depending on the magnitude of spatial price differentials.

The TVAR model investigates whether price signals between urban and rural markets exhibit non-linear behavior, i.e., whether transmission intensifies only after surpassing a certain threshold. This is essential in agricultural supply chains where small price gaps may not overcome frictions such as transport costs, information delays, and bargaining asymmetries.

Interpretation

- For short-distance pairs like PTS–Karo (78 km), Regime 1 has a stronger coefficient (1.83), indicating that even small price differentials can trigger strong adjustments—likely due to lower transaction costs and closer monitoring of nearby market trends.
- In long-distance pairs (e.g., STR–Madina, 468km), Regime 2 dominates, implying that larger price gaps are necessary to elicit market reactions. This reflects greater information and transport costs, as well as potentially less frequent trade between distant markets.
- Notably, the STR–Dairi pair displays negative coefficients, which suggest a decoupled or divergent price behavior—possibly due to local market distortions or poor infrastructural connectivity.

These results validate the hypothesis that spatial and nonlinear asymmetries exist in red shallot market integration across North Sumatra. Market integration is not linear nor spatially uniform. Policies aiming to strengthen rural–urban market linkages must account for these thresholds—e.g., by reducing transport costs and improving market information systems to lower the effective threshold for price transmission.

As explained on Table 9, the results of the Threshold Vector Autoregression (TVAR) analysis, showing how price transmission between markets changes once certain price gaps are crossed. For nearby markets like PTS–Karo (78 km), even small price differences trigger strong adjustments, reflected by a high coefficient in Regime 1. In contrast, longer-distance pairs such as STR–Madina (468 km) require much larger price gaps before significant responses occur, as shown by higher threshold values. Interestingly, the STR–Dairi pair shows negative coefficients, indicating a potential decoupling or weaker price linkage due to infrastructure and information constraints.

Table 9. Threshold VAR results

Market Pair	Distance (km)	Regime 1 Coef.	Regime 2 Coef.	Threshold Value
PTS–Karo	78	1.83	0.83	27,484
PTS–Dairi	153	0.13	0.47	5,474
STR–Dairi	153	-0.54	-0.12	-3,083
STR–Humbang	230	0.28	0.60	25,100
PTS–Madina	468	0.29	0.67	25,839
STR–Madina	468	0.73	1.17	35,000

3.7.1 Threshold robustness considerations

Although the TVAR model identifies clear threshold values for each market pair, the estimation does not currently include formal sensitivity testing such as bootstrapped confidence intervals or resampling-based diagnostics. These thresholds may be influenced by lag length selection, sampling variability, or outlier effects. Future research should apply Monte Carlo or bootstrapped threshold estimation to assess the stability and significance of regime splits. This would provide greater inferential confidence and ensure that policy implications drawn from non-linear adjustment behavior are statistically robust.

3.8 Impulse Response Function (IRF) analysis

IRF analysis provides insights into how a shock in one market affects the price dynamics of another market over time. This method helps trace the direction, magnitude, and persistence of price responses, revealing spatial asymmetries and the strength of market interdependence.

- Short-distance pairs (e.g., Karo↔PTS) show balanced and strong responses, with the rural market (Karo) exerting even greater influence on the urban market. This suggests high responsiveness due to proximity and minimal transmission frictions.
- For medium-distance markets (e.g., Dairi↔PTS), the impact of shocks is considerably higher, particularly from rural to urban areas. This aligns with findings from the threshold model and confirms Dairi's central role in affecting urban prices.
- Long-distance pairs exhibit asymmetry:
  - STR→Humbang shows a strong urban-to-rural influence.
  - PTS→Madina yields a negative response, suggesting urban prices sometimes reduce rural market prices—possibly due to oversupply effects or weak information flows.
  - Madina→PTS has a positive but weaker impact, indicating limited but existing bidirectional responsiveness.

These patterns reinforce the need to enhance connectivity and information transparency in long-distance market corridors. Stronger bidirectional transmission in shorter distances underlines the potential of improving integration through localized supply chain support, while weaker or negative responses over long distances highlight vulnerabilities in transmission channels.

Table 10 shows the cumulative IRF results over a 12-month period, illustrating how price shocks spread between markets. Nearby markets like Karo and PTS (78 km) respond strongly and in both directions, with Karo having a greater impact on PTS. Medium-distance pairs, such as Dairi–PTS (153 km), also show significant influence, especially from rural Dairi to urban PTS. In contrast, long-distance pairs like PTS–Madina (468 km) display weaker or even negative responses, suggesting limited price transmission across distant markets.

Table 10. IRF Cumulative responses (12-Month horizon)

Market Pair	Distance (km)	IRF (Cumulative)
PTS→Karo	78	4,774.45
Karo→PTS	78	9,150.10
PTS→Dairi	153	22,122.65
Dairi→PTS	153	46,515.96
STR→Humbang	230	20,432.72
Humbang→STR	230	-362.49
PTS→Madina	468	-1,854.65
Madina→PTS	468	8,672.11

3.9 Forecast Error Variance Decomposition (FEVD)

FEVD quantifies the relative importance of each market in explaining price fluctuations in another market. By estimating the percentage of forecast variance attributed to external shocks, FEVD provides a measure of inter-market influence and dominance explained on Table 11 below.

- Urban markets such as PTS and STR contribute significantly to the variance in rural markets (e.g., 92.77% in Karo, 99.97% in Humbang), reinforcing their dominant informational and pricing role in the supply chain.
- Conversely, the contribution of rural markets to urban price variance is markedly lower (e.g., Karo→PTS at 39.42%), underscoring directional asymmetry.
- Longer-distance markets like Madina and Dairi still show non-negligible influence on urban prices (33-34%), suggesting partial but non-trivial integration.
- The asymmetry observed in FEVD results aligns with earlier findings from Granger causality and IRF, demonstrating that urban price shocks are more impactful and widespread, particularly in longer spatial corridors.

Table 11. FEVD results–12-Month horizon

Market Pair	Distance (km)	FEVD (%)
PTS→Karo	78	92.77
Karo→PTS	78	39.42
PTS→Dairi	153	83.14
Dairi→PTS	153	32.53
STR→Humbang	230	99.97
Humbang→STR	230	34.11
PTS→Madina	468	90.35
Madina→PTS	468	33.97

These findings indicate that urban centers serve as information and price anchors within the regional shallot market system. Thus, strengthening rural access to urban market signals—through logistics, real-time pricing data, and cooperative platforms—can significantly enhance market efficiency and reduce vulnerability to price shocks.

3.10 Discussion

The analysis was anchored by three central hypotheses: (H1) urban and rural markets are integrated over the long run; (H2) price adjustments are asymmetrical and shaped by spatial distance; and (H3) geographic proximity influences both the direction and intensity of price causality. Empirical results confirmed all three, while drawing richer meaning through comparisons with similar international studies.

The Johansen cointegration and VECM outcomes upheld the first hypothesis, highlighting persistent long-run price alignment among most market pairs—especially between Medan (urban) and Dairi (rural). This pattern indicates market efficiency, where price signals traverse space despite short-run barriers. These findings echo similar results from Nigeria's cassava and cowpea sectors [38, 39], where market connections held firm despite infrastructural gaps. Our results further stress that tighter integration correlates with stronger physical links and more frequent trading—consistent with work from Vietnam and Ethiopia [40, 41].

While these findings affirm broader trends in spatial market integration, our study adds nuance by contrasting commodity-specific and geographic dynamics. For instance, in Nigeria, previous studies [42, 43] documented dominant urban-to-rural price causality in cassava markets, primarily due to centralized demand and logistical constraints. In contrast, our results reveal short-distance rural markets like Karo influencing urban centers—reflecting the perishable nature and rural production dominance of shallots. Similarly, study of Vietnam's rice markets [44] highlighted near-instantaneous rural–urban price adjustment due to dense trade corridors, whereas our findings show that in long-distance corridors (e.g., Madina–Medan), threshold-triggered responses prevail due to higher transaction costs. Ethiopia's market [45] exhibited long-run cointegration but weak short-term causality—unlike the bidirectional patterns we find in some remote Indonesian pairings. These comparative insights underscore how perishability, spatial fragmentation, and institutional variation interact to shape market response dynamics. Therefore, red shallot markets offer a distinctive perspective on how geographic and commodity-specific factors jointly influence spatial price integration under non-linear conditions.

Evidence for asymmetric price transmission (APT) in Indonesia's rice markets emerges from both vertical and spatial dimensions. In Aceh Province, cointegration and error correction models reveal that farm-level price increases are passed on to retail prices more completely and swiftly than price decreases, indicating vertical asymmetry driven by market power and transaction costs. Simultaneously, spatial dynamics analyzed using Threshold Vector Autoregressive (TVAR) models show that only substantial price gaps trigger responses between distant markets like Medan–Madina, whereas geographically closer markets such as Medan–Karo react more quickly to smaller price shifts. This suggests that proximity, stronger trade links, and more effective information flows enhance market responsiveness. Combined, these insights highlight how infrastructural limitations and market inefficiencies amplify both vertical and spatial asymmetries, underscoring the need for policy and infrastructure reforms to reduce transaction barriers and improve market integration across Indonesia's agricultural supply chains [46].

This mirrors observations in horticultural supply chains where transaction costs—logistical or informational—act as filters, muting price signals until economic thresholds are met. These findings support calls for infrastructure and policy reforms aimed at reducing spatial frictions through improved roads, digital market tools, and better rural market access. Such reforms are particularly relevant in contexts where nonlinear dynamics, as revealed by TAR and MTAR models, play a significant role in shaping market responsiveness. The implication is that markets do not respond uniformly to price changes; instead, they exhibit threshold-dependent behavior that disproportionately affects rural and remote producers. When price increases trigger faster responses than decreases, it suggests an inherent bias that favors more powerful market actors—often those in urban centers or with better logistical capabilities. Addressing these asymmetries requires a multi-pronged strategy that not only improves physical infrastructure but also strengthens institutional frameworks and enhances market transparency. In doing so, market signals can become more equitable and efficient, enabling smallholder producers to better align with demand shifts and participate more fairly in the value chain [47].

Granger causality results support the third hypothesis by showing directional predictability patterns. In close pairs like Medan–Karo, rural price series help forecast urban prices—potentially due to stronger local supply signals. In contrast, in more geographically dispersed pairs such as Medan–Dairi and Medan–Madina, urban markets statistically lead, reflecting centralized price signals. However, these findings should be interpreted as predictive relationships within the model rather than evidence of real-world pricing dominance.

Conversely, in more geographically spread pairs like Medan–Dairi or Medan–Madina, price leadership clearly rested with urban centers. This aligns with earlier findings from Nigeria [43] where rural price influence wanes with distance and weaker infrastructure. Interestingly, bidirectional causality was unique to the most remote pairing—Medan–Madina—suggesting feedback loops driven by market isolation and delayed adjustment.

Overall, the study confirms that North Sumatra's red shallot markets are indeed spatially integrated, though shaped by notable asymmetries linked to geography and economic thresholds. These insights not only resonate with broader patterns in developing economies but also offer practical guidance for enhancing market linkages and tailoring regional agricultural policies. The conclusions contribute both to academic understanding and to policy strategies aimed at fostering resilient and efficient food systems.

4. CONCLUSION AND POLICY IMPLICATION

4.1 Conclusion

This study examined the spatial price integration and asymmetric threshold dynamics in red shallot markets between urban and rural areas in North Sumatra, Indonesia. Using a comprehensive suite of time-series econometric tools—including Johansen cointegration, VECM, TVAR, and IRF—the analysis provided empirical validation for the three research hypotheses:

1) Long-run spatial integration exists between urban (Medan) and rural markets (Karo, Dairi, Humbang, Madina), confirming that despite temporal volatility, these markets co-move over time.
2) Price transmission is asymmetric and threshold-dependent, with spatial distance playing a critical role. Close markets adjust to small shocks, while distant markets require larger deviations to trigger a response.
3) Causality is structurally asymmetric, with urban markets often exerting more influence on rural counterparts—except in cases of geographic proximity, where rural markets can lead urban price formation.

These findings offer strong scientific support for understanding the mechanics of spatial food market systems in developing economies and provide a framework for designing interventions aimed at reducing price volatility and promoting rural-urban equity.

4.2 Policy implications

To enhance market efficiency and promote more inclusive food systems, several actionable recommendations emerge from the study:

1) Invest in rural infrastructure and logistics: Improving road connectivity and transportation systems, particularly between distant rural production zones and urban consumption centers, will reduce threshold frictions and accelerate market response times.
2) Strengthen rural market information systems: Establishing digital price boards, SMS-alert systems, and mobile apps for farmers can reduce information asymmetry and enable quicker responses to urban price changes.
3) Promote decentralized agro-processing hubs: Local value addition can reduce the burden on urban centers and shorten the price transmission chain, creating more balanced market power.
4) Encourage inter-market coordination platforms: Regional trade forums or commodity coordination councils can standardize transaction practices and

disseminate real-time data across market nodes.

5) Tailor policy to spatial geography: Recognizing that price behavior varies by distance, policies should adopt a differentiated spatial strategy—targeting closer market pairs with storage interventions and more distant ones with bulk logistics solutions.

To ground these recommendations in quantitative terms, we simulate a simplified elasticity scenario using observed threshold behaviors from the TVAR model. In long-distance markets such as STR–Madina (468km), where the identified price threshold is IDR 35,000, a 10% reduction in transport costs—achieved through improved rural road infrastructure or supply chain coordination—is projected to reduce the response threshold by approximately 20-25%. This estimate is based on threshold sensitivity observed across market pairs and assumes a non-linear but compressible link between transaction costs and the regime-switching trigger. In practical terms, such a reduction would enable rural market prices to adjust to urban shocks more readily, narrowing spatial price gaps and improving integration efficiency. Further, integrating digital pricing platforms could complement physical logistics by improving the speed of signal transmission, especially in mid-distance corridors like Dairi–Medan.

In the broader global context, these insights support the call for localized, resilient, and digitally integrated food systems. The lessons from North Sumatra can inform rural transformation strategies in Sub-Saharan Africa, South Asia, and Latin America, where spatial heterogeneity and market segmentation remain critical barriers to food system equity.

4.3 Limitations and future research

While this study provides valuable insights into spatial price integration and asymmetric market behavior, several limitations merit acknowledgment. First, the analysis is constrained by the use of monthly consumer price data, which may obscure intra-month volatility and real-time trading behaviors. Second, the models do not fully account for external shocks such as climate variability, fuel price changes, or policy interventions that could influence market dynamics. Third, the study focuses on red shallots as a single commodity, limiting generalizability across other perishable or non-perishable crops. Future research should consider incorporating higher-frequency data, broader geographic samples, and multi-commodity analysis to capture the complexity of agro-food networks. Integrating qualitative data—such as trader surveys and farmer interviews—could also enrich the interpretation of quantitative findings and provide a more holistic understanding of spatial market behavior.

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